Simulation Modelling Practice and Theory 146 (2026) 103228

Contents lists available at ScienceDirect

Simulation Modelling Practice and Theory

journal homepage: www.elsevier.com/locate/simpat

The impact of import container flow characteristics on port operational efficiency

Agostino Bruzzone [a], Alessia Giulianetti [b], Marco Gotelli [a], Anna Sciomachen [b],*

[a] Department of Mechanical, Energy, Management and Transport Engineering, University of Genoa, via Opera Pia 15, Genoa, 16145, Italy
[b] Department of Economics and Business Studies, University of Genoa, via Vivaldi 5, Genoa, 16126, Italy

ARTICLE INFO

Keywords:
Marine container terminal
Import flow
Discrete event simulation
Scenario generation
Synthetic data
Performance indices

ABSTRACT

In this paper, we analyze different scenarios for container flows arriving at marine terminals to different destinations in the hinterland. The aim of the study is to verify how the type of import containers — standard, hazardous, and refrigerated — and their size affect the operational efficiency of the terminal. Relevant performance indicators, such as container dwell time, average and maximum number of waiting containers, and equipment utilization rate, are evaluated. To this end, we present a discrete-event simulation study that, although generalizable to any port, refers to a terminal in the port network of Genoa (Italy). The number of considered scenarios, illustrated in this paper, are taken from a synthetic data generator for logistics flows and used in Witness Horizon v.24 simulation software environment to execute independent runs at a steady state condition. To the authors' knowledge, this is the first time that a sensitivity analysis based on the variation in the types of containers is presented. The performed simulation experiments can be of great interest to various port stakeholders. Indeed, the results show that the percentage composition of the type of import container over the annual time horizon considered has an impact on the indicators under analysis, favoring a more balanced distribution. However, again in relation to the same indicators, the variation in container size appears to be negligible. The study highlights how advance knowledge of the type of import containers can support port terminal management in terms of efficient management and optimization of resources, providing specific advice on the operational decisions concerning equipment and block yard allocation.

1. Introduction

Maritime routes have been a predominant method of trade for centuries. Today, freight transport by sea continues to grow, emphasizing the crucial importance of efficient maritime logistics. In this context, port terminals are crucial nodes in the maritime supply chain. The efficiency and capacity of ports directly influence global trade flow, economic stability, and the ability to meet the increasing demands of international commerce, facilitating the transfer between sea and land transport systems. The operation of marine terminals is one of the key areas where the need to implement new solutions and develop simulation models to study and optimize goods flows is crucial to remain competitive in the economic landscape. Recently, numerous studies have gone in this direction. Among others, the need to efficiently manage the flow of goods within container terminals and between ports and the hinterland is emphasized in [1,2], while the need for reliable forecasts in the management of ports operations is discussed

* Corresponding author.
E-mail addresses: agostino.bruzzone@unige.it (A. Bruzzone), alessia.giulianetti@edu.unige.it (A. Giulianetti), marco.gotelli@unige.it (M. Gotelli), sciomach@economia.unige.it (A. Sciomachen).

https://doi.org/10.1016/j.simpat.2025.103228
Received 17 March 2025; Received in revised form 7 November 2025; Accepted 11 November 2025
Available online 12 November 2025
1569-190X/

in [3]. Operational decisions concerning equipment scheduling and storage area allocation are addressed in [4–6]. The use of decision support systems is also suggested in [7] to plan storage and operations in bulk terminals. Further, cost shipping reduction of international container shipping companies while avoiding unnecessary transshipment and displacement operations is considered in [8], while the impact of governance on the technical efficiency of container ports is analyzed in [9].

In this paper, we present a discrete-event simulation study, developed with Witness Horizon v.24 software environment, to analyze how the type and size of containerized import flows impact on the performance indices of the terminal mainly affecting its efficiency, such as dwell time and equipment utilization rate. As a novel issue, the study highlights the role of integrating advanced simulations and data analysis to provide decision-makers with robust quantitative analysis for terminal operations management policies. Moreover, at least to the authors' knowledge, this is the first time that a sensitivity analysis based on the variation of the above mentioned parameters of containers imported has been presented. Therefore, this paper aims to fill this gap with regard to an in-depth analysis of how different combinations of import container flows affect the operation of a container terminal. Since the proposed case study can be generalized to any container terminal, we believe that the results presented are very useful for both terminal operators and port stakeholders. In fact, they provide useful preventive information for reorganizing both yard space and equipment allocation more efficiently, based on import flows, thus enabling them to cope with competition.

The remaining of the paper is as follows. The literary review related to the topic addressed in the present study is reported in Section 2. Section 3 presents in detail the problem under study, while Section 4 describes the proposed simulation model and how the input data related to the import flow of containers are derived. Section 5 reports the experimental results of the simulation study and related discussion. Finally, Section 6 concludes the paper.

2. Related literary review

2.1. Simulation studies for port efficiency assessment

Other simulation studies have been recently presented to evaluate the efficiency of a marine terminal depending either on the size of the ships (see, e.g. [10,11]) or on the operation equipment and infrastructure (see, e.g., [12–14]). In [15] the authors propose a simulation model that includes detailed descriptions in the transportation network to evaluate different scenarios for road design terminals and truck fleet size. Witness Horizon has also been successfully employed in studies such as [16], which focuses on container terminal logistics systems, to simulate and optimize port operations. A study to define the optimal schedule of train departure from a terminal is proposed in [17]. As a novel issue, considering the same terminal, located in the port network of the city of Genoa, Italy, and given the characteristics of the import containers, such as, origin, destination, and inland transport modality, in the present study we focus on the container types and sizes to see how much are relevant for possible critical issues in improving the operational efficiency of the terminal. In fact, at least known to the authors, no results have been presented in the literature on how the type of containers arriving at a terminal impact its performance. Some recent works in the literature on this subject concerns Ro-Ro terminals. Among others, [18] presents a framework to create decision support models based on simulation, taking into account the typical functional and physical organization of pure Ro–Ro terminals and their flows, while [19] proposes a simulation model for assessing the impact of Ro-Ro terminal management decisions on the efficiency of terminal planning and operations, considering the total cost of transit-generated traffic as a performance indicator. Further, terminal capacity analysis is performed in [20,21], where Ro-Ro terminals are considered. The critical aspect played by limited capacity of a port is highlighted in [2].

2.2. Other methodological approaches for port efficiency

From a methodological point of view, not only discrete event simulation, but also machine learning (ML) and integrated simulation and optimization approaches have been successfully proposed since the beginning of this decade to assess the efficiency of port terminals. Among others, the role of optimization in container stacking operations is discussed in [22–24], where new models and algorithms are proposed. An innovative approach presented by Bruzzone et al. in [25] involves strategic engineering, a new discipline that combines simulation, optimization, artificial intelligence (AI), and data analytics in a closed-loop to support decision makers. The combination of these disciplines has recently been successfully applied for analyzing complex marine logistics systems, and for evaluating and improving relevant performance indices of container terminals. As highlighted in the literature review [26], the integration of simulation and optimization approaches has shown great potential in maritime logistics, particularly in addressing terminal operations, shipping lines, and hinterland transport processes. Among others, in [27] a simulation–optimization study is presented to determine the most efficient yard layout in automated container terminals. A dynamic truck dispatching system for container ports equipped with Real2Sim simulation and a truck dispatch agent is proposed in [28]. The scheduling of unmanned shipment vessels in automated container terminals is faced in [29] using a multi-attention reinforcement learning algorithm. An integration of ML and simulation for scheduling truck arrivals in a port is presented in [30].

2.3. Data flow generation for port indices evaluation

It is worth noting that to apply the above mentioned methodologies to container flow analysis and the study of improvement strategies, it is essential to collect valuable data and information. However, this sector often faces a lack of historical data and reluctance from organizations to share details of traffic and extensive statistics due to confidentiality feelings and competitive attitude. This is especially true in containerized traffic, which is characterized by highly competitive realities, often specialized according to flows, types, and areas of origin and destination of containers. The problem of vessel arrival time prediction to ports is faced in [31], where ML models are proposed for the efficiency of marine terminal operations. In [32] the authors analyze the available data to determine for each ship that arrived at the port of Antwerp which parameters affect the expected time arrival (ETA) deviations. An evolutionary game algorithm is presented in [33] to construct an adaptive allocation method of terminal container parameters. A deep reinforcement learning approach is developed in [34] to optimize relocation policies based on predictions. How data science using operational data can improve container terminal operations is investigated in [35]. Literature on the interplay of operations research and big data analytics in container terminals is presented in [36]. Indeed, it is crucial to develop models and methods to create realistic and consistent data relying on current and future scenarios. To address this need, a scenarios generator of logistics flow (GOLF) from open data (OD) using AI able is introduced in [37]. The generation of synthetic data has proven indispensable to overcome the scarcity of real-world data. For example, the ConFlowGen tool [38–40] has been successfully applied to generate synthetic but realistic traffic scenarios for the Tollerort container terminal (TCT) in Hamburg, focusing on the specific characteristics of that port. Similarly, studies such as [41] demonstrate how synthetic data generation techniques significantly enhance the performance of machine learning models, particularly in scenarios where real data are limited.

In the simulation model proposed in the present study we integrate the synthetic data provided by GOLF [37] to derive the attribute of the containers, as reported later. GOLF estimates container demand at the node level by learning coefficients that map proxy variables (resident population, industrial density, presence of manufacturing and logistics activities, and other economic indicators) to expected container flows. A supervised ML model is trained on observed data to estimate these coefficients and then applies them across all territorial nodes to define potential origin and destination demand. The resulting demand estimates serve as inputs to the scenario generator, which allocates flows to destinations and specifies the composition used in the simulation experiments.

3. Operational context and problem statement

The purpose of our research is to build a simulation model of the flow of containers being imported into a marine terminal. In the simulation, we focus exclusively on the flow of containers from their arrival at the quay, through the terminal and loading operations, to be shipped to the hinterland. In fact, the proposed analysis aims to evaluate container handling efficiency, mainly to improve key performance indicators (KPIs) associated with inland forwarding operations. The simulation model is performed using Witness Horizon v.24 as a software tool, whose functionalities are described in [42,43]. Since the first decade of this century, Witness has already been successfully used as a support tool for decision makers and planners within terminals and seaports (see, e.g. [11,17,44–47] among others). The present model aims to describe the main stages of the process, from the arrival of containers at the quay to their handling and distribution to the intermodal terminals served. As described in the next section, in this work we refer to the PSA Genoa PRA terminal. However, the proposed methodology can be applied to any other container terminal as well. In fact, the proposed model presents the container handling processes, from the quay to the storage areas in the terminal, and from there to the interfaces with the hinterland, i.e., truck gates and railway yards, which are common to most container terminals. Furthermore, the handling equipment used and the relative timing are parameters of the model and can therefore be adapted to any context. In particular, in the simulation model implemented with Witness Horizon, handling equipment is represented by predefined components that allow entering not only the relative cycle times but also the rules governing how containers are picked up or positioned, possibly expressed by functions and conditions, such as state dependent rules or the need for synchronization with other means of transport. It should be noted, however, that the dynamics of the model are designed for container terminals, and therefore the model cannot be applied to bulk or RO-RO terminals. In the development of the model, several key operational variables are identified, closely related to the characteristics of containers and their management at the terminal. Fig. 1 shows an outline of the container flow under analysis. In the simulation, the flow starts with the arrival of the containers at the quay, where they are unloaded from the ships. Containers are then sorted into different storage areas according to their characteristics. The containers destined for rail transport are sent to the railyard where they are loaded onto trains to be transported to the respective intermodal terminals, while containers intended for transport by truck are transported out of the terminal by dedicated vehicles. Containers are classified according to three main types, namely standard, hazardous and reefer. Empty containers are also considered an additional type. Hazardous containers require specific safety measures for handling and storage, following stricter rules and regulations to avoid accident risks. The reefer containers, on the other hand, require controlled temperature conditions and adequate energy resources, posing an additional burden on the terminal. Particular attention is also paid to empty containers, which, as illustrated in Section 3, are stored in a dedicated area of the yard. Within the above-mentioned main classification of containers, based on how they are sorted within the terminal, in this work we associate each container with parameters relating to their type, size, mode of transport used for their forwarding, and their origin and destination pair.

The main objective of this simulation is to analyze terminal performance as these characteristics of generated container flow change, enabling better planning and management of terminal resources. Through the simulation model, it is possible to evaluate the impact of different operational scenarios and assess key performance indices (KPIs), such as dwell time and storage area capacity utilization rate. The definition of the problem results in the need for a model that represents the flow of containers at all operational stages, allowing for the analysis of interactions between operational variables and KPIs, and providing a basis for improving the performance of the terminal under study.

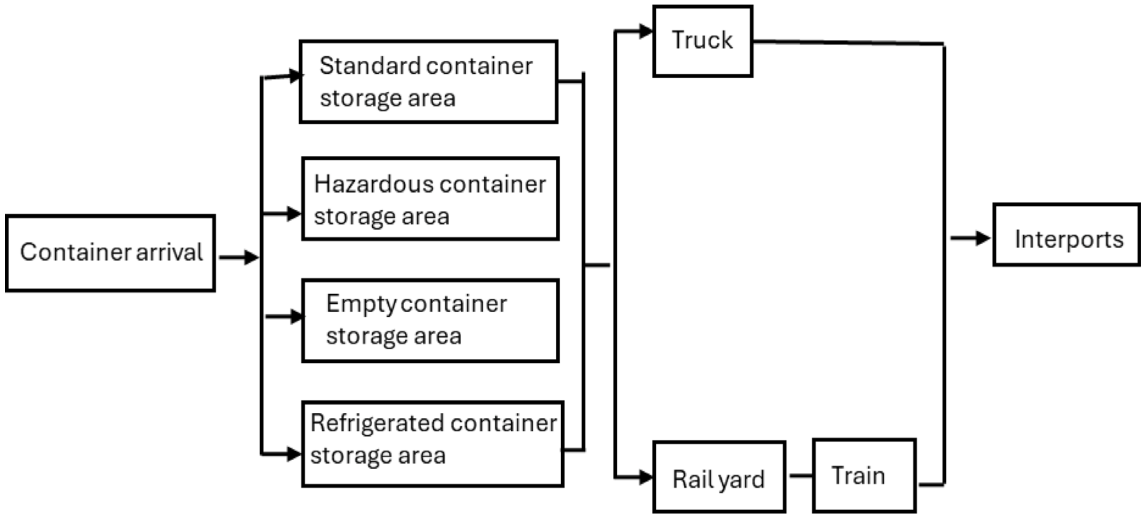

Fig. 1. Outline of the flow under analysis.

4. Simulation model

The discrete-event simulation model, developed using Witness Horizon v.24 software environment, is structured around three key components: parts, representing the elements flowing within the system; machines, which perform the activities performed in the system; and buffers, corresponding to the physical spaces for collecting parts. These three elements work together to replicate the system dynamics. In the following, a detailed technical explanation of the model components and their interactions are provided to enhance understanding of its functionality.

As illustrated in Fig. 2, the simulation model represents the import flow of containers, considering both the different classes of containers and the transport modalities to their destined intermodal terminals. The model includes twenty-seven buffers: eighteen representing intermodal terminals of destination and nine representing the terminal yards. It is important to note that the buffer component in a simulation model implemented in Witness Horizon refers to an element used both to temporarily contain parts and to represent physical spaces. For this type of element, regardless of what it represents, the indices of interest associated with it are automatically determined, such as the average dwell time, the average number, the minimum and the maximum number of parts contained within it. To simulate container handling, four types of machines were configured based on their specific functions: terminal tractors, trucks, rail-mounted gantry cranes (RMGs), and assembly machines for trains. Each machine, depending on the specific equipment it represents, is associated with the corresponding cycle time and the input and output rules with which they pick up and place parts in the system.

Inside the simulation model, containers are defined as active parts. To simulate their arrival at the terminal quay, containers are generated considering an average inter-arrival time of two minutes, following a NegExp distribution. At their arrivals, containers are stored in blocks in the area dedicated to them. It is important to emphasize that in this study we do not consider the ship arrival times and the subsequent unloading process of containers. Instead, we consider the inter-arrival time of containers based on the annual import flow volume data from [48] by the Genoa Port Authority.

Each container is associated with the following five attributes; they define its movement inside the terminal and destination:

1. type of transport: each container is assigned to rail or truck transport mode;
2. container size: 20-foot and 40-foot containers are distinguished;
3. container status: each container can be empty or not-empty;
4. container destination: depending on the type of transport, each container is destined for an intermodal terminal, served by the specific type of transport;
5. type of container: standard, refrigerated and hazardous containers are considered.

The generation of the above attributes of each container is implemented in the simulation model as is shown in Fig. 3. Note that these container attributes affect both the type of storage area and the handling time during the simulation.

The assignment of the above attributes to each container is performed in three subsequential steps. First, attributes 1–3 are assigned independently of each other based on the percentage distributions reported in the port of Genoa data [48], as detailed in Table 1. Note that due to the random nature of the generation of each container, each simulation run is characterized by a significant variation in the number of containers of each type generated, even within the same scenario.

In the second step, the destination of the container (attribute 4) is assigned based on attribute 1, meaning that the possible destinations are determined by the type of transport previously assigned. Since no direct data is available in the mentioned

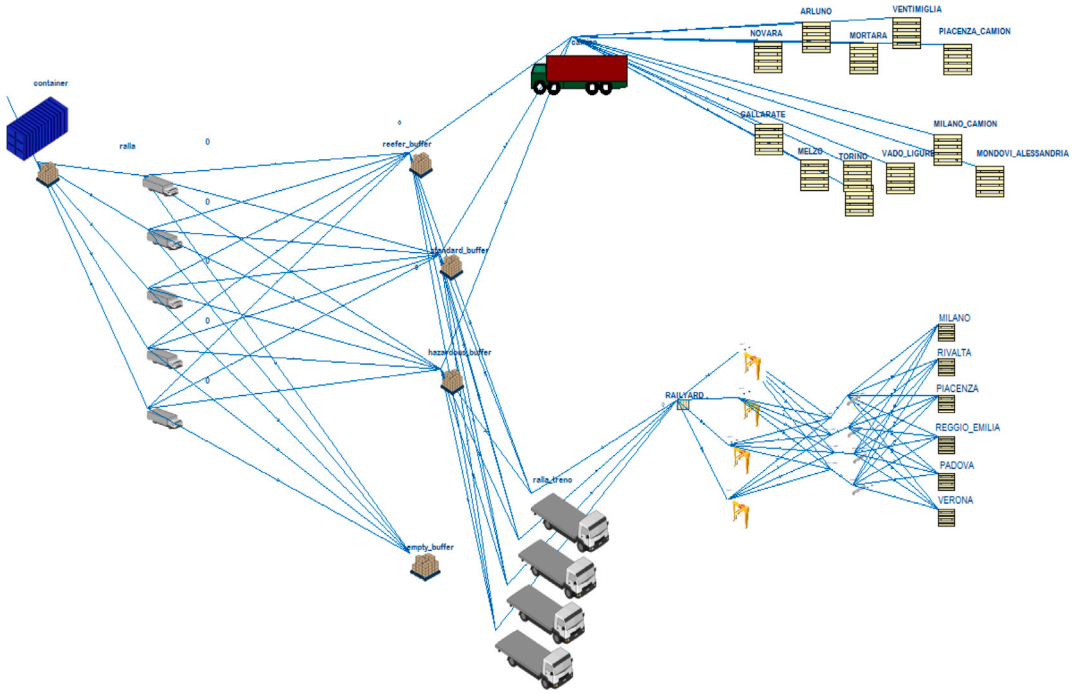

Fig. 2. Layout of the simulation model.

```
DIM index_perc1 AS REAL
DIM index_perc2 AS REAL
DIM index_perc3 AS REAL
DIM index_perc4 AS REAL
DIM index_perc5 AS REAL
!
index_perc1 = Random (0,1)
index_perc2 = Random (0,1)
index_perc3 = Random (0,1)
index_perc4 = Random (0,1)
index_perc5 = Random (0,1)
!ASSIGN THE ATTRIBUTE EMPTY OR FULL 1= EMPTY
IF index_perc1 < P_EMPTY
 container_empty = 1
ELSE
 container_empty = 0
ENDIF
!container type 1=standard 2=hazardous 3=reefer
IF container_empty = 0
 IF index_perc5 < P_STANDARD
  container_type = 1
 ELSEIF index_perc5 < P_STANDARD + P_HAZARDOUS
  container_type = 2
 ELSEIF index_perc5 <= 1
  container_type = 3
 ENDIF
ENDIF
```

```
!ASSIGN THE DIMENSION
IF index_perc2 < 0.3
 container_dimension = 20
ELSE
 container_dimension = 40
ENDIF
!
!ASSIGN THE ATTRIBUTE TRAIN OR TRUCK
IF index_perc3 < 0.847
 transport_type = 1


ELSE
 transport_type = 2

ENDIF
```

```
!ASSIGN THE DESTINATION BY TRUCK
IF transport_type = 1
 IF index_perc4 < 0.08
  container_destination = 1
 ELSEIF index_perc4 < 0.11
  container_destination = 2
 ELSEIF index_perc4 < 0.14
  container_destination = 3
 ELSEIF index_perc4 < 0.21
  container_destination = 4
 ELSEIF index_perc4 < 0.26
  container_destination = 5
 ELSEIF index_perc4 < 0.31
  container_destination = 6
 ELSEIF index_perc4 < 0.33
  container_destination = 7
 ELSEIF index_perc4 < 0.35
  container_destination = 8
 ELSEIF index_perc4 < 0.65
  container_destination = 9
 ELSEIF index_perc4 < 0.71
  container_destination = 10
 ELSEIF index_perc4 <= 1
  container_destination = 11
 ENDIF
ENDIF
```

```
!ASSIGN THE DESTINATION ON A TRAIN
IF transport_type = 2
 IF index_perc4 < 0.28
  container_destination = 1
 ELSEIF index_perc4 < 0.33
  container_destination = 2
 ELSEIF index_perc4 < 0.35
  container_destination = 3
 ELSEIF index_perc4 < 0.53
  container_destination = 4
 ELSEIF index_perc4 < 0.67
  container_destination = 5
 ELSEIF index_perc4 < 0.1
  container_destination = 6
 ENDIF
ENDIF
```

Fig. 3. Attribute assignment to container on Witness.

above port of Genoa reports, the required distribution percentages for different intermodal terminals are derived from the ContainerFlow_Simulator data file GOLF previously described [37]. The resulting destination distribution is detailed in Table 2.

Finally, attribute 5 is assigned, representing a key aspect of our research, as its distribution varies to generate different scenarios for comparative analysis at the end of the simulation experiments. This attribute defines the categorization of non-empty containers into hazardous, reefer and standard ones, shaping the composition of each scenario, following the percentage distributions defined

Table 1
Percentage distribution of the attributes from one to three.

Attribute	Type	Percentage
Type of transport	Train	15,3%
	Truck	84,7%
Container size	20′	30%
	40′	70%
Container status	Empty	37%
	Not Empty	63%

Table 2
Percentage distribution of destination attribute.

Type of transport	Destination	Percentage
Train	Milano	28%
	Rivalta	5%
	Piacenza	2%
	Reggio Emilia	19%
	Padova	13%
	Verona	33%
Truck	Novara	8%
	Gallarate	3%
	Arluno	3%
	Melzo	8%
	Mortara	5%
	Vado Ligure	5%
	Ventimiglia	2%
	Mondovìe Alessandria	2%
	Torino	29%
	Piacenza	6%
	Milano	29%

Table 3
Scenarios under analysis.

	% Empty	% Standard	% Reefer	% Hazardous
Scenario 1	37%	52.48%	5.42%	5.10%
Scenario 2	30%	58%	6%	6%
Scenario 3	30%	46%	12%	12%
Scenario 4	30%	35%	18%	17%
Scenario 5	30%	24%	23%	23%
Scenario 6	30%	70%	0%	0%

as shown in Table 3. Thus, this variation allow us to model different operating conditions and assess their impact on terminal efficiency.

In Scenario 1, 37% of containers are empty, according to data reported in [48], while the percentages of non-empty containers are calculated based on the relative capacities of the storage areas dedicated to each type of container. Thus, this scenario reflects a distribution consistent with the port under analysis infrastructure and logistics constraints. Beginning with Scenario 2, the percentage of empty containers is chosen to be reduced to 30%, assuming an optimization of the occupancy of available space in the terminal and an increase in the handling of actual cargo, in line with strategies of greater logistical efficiency. Keeping this share constant, in Scenarios 2 to 5 the share of standard containers is progressively reduced, increasing instead the presence of reefers and hazardous, until a balanced distribution among these three categories is reached in Scenario 5. This approach makes it possible to assess the impact of a more diversified use of port infrastructure, simulating a more balanced management of different types of containers. Finally, in Scenario 6, the quota of standard containers increases significantly, becoming the predominant category among non-empty containers, while reefers and hazardous containers are not present, reflecting an assumption of maximizing the space dedicated to this specific type.

After entering the system, containers are transferred to separate storage areas, represented in the simulation model by buffers as specified above. More precisely, four different buffers have been considered, each one for a given container type. Their capacities are inserted according to what is reported in [49] and given below:

- Storage area for hazardous containers, capacity 1408 containers.
- Storage area for refrigerated containers, capacity of 1500 containers.
- Storage area for standard containers, capacity 14,500 containers.

Table 4
Graphical representation of the densities of the cycle times of the terminal tractors.

Type of container	From berth to storage area	From storage area to railyard
Standard containers	*TNormal (6,1,2,10)*	*TNormal (6,1,2,10)*
Refrigerated containers	*TNormal (8,2,6,15)*	*TNormal (8,2,6,15)*
Hazardous containers	*TNormal (10,2,8,20)*	*TNormal (8,1.5,6,14)*

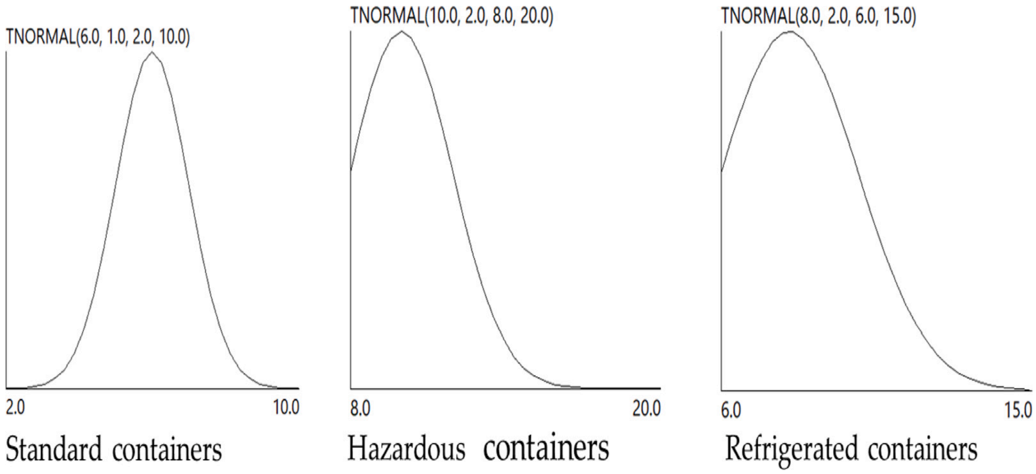

Fig. 4. Graphical representation of the densities of the cycle times of the terminal tractors.

- Storage area for empty containers, capacity 10,224 containers. Note that, since the exact figure is not available, this value, which corresponds to 37% of the total capacity of the yard, has been calculated based on the number of containers handled each year, as reported in the Genoa port report [48].

Container movements within the terminal are managed by terminal tractors. They are used to move containers from the berth to their respective storage areas. As soon as a container is unloaded, the first available tractor goes to pick it up. Each container is associated with a specific processing time attribute, which depends on the distance to be traveled, and the type of container handled. Since terminal tractors operate at a constant average speed within the terminal and can handle different types of containers, their cycle time varies dynamically based on the characteristics of the transported container. To accurately model this variability while maintaining realistic operational constraints, we adopted a truncated Normal distribution (TNormal) for processing times. In fact, handling times at a terminal tend to cluster around a typical value, as they are influenced by structured operating procedures and constraints such as predefined routes and standardized positioning activities but at the same time, there is variability due to small differences in execution times. Consequently, a truncated normal distribution is chosen, ensuring that processing times remain within a range while capturing the stochastic nature of container handling operations. Considering the location of the yard of the different types of containers in the terminal, the resulting cycle times of the terminal tractors are reported in Table 4. Fig. 4 illustrates the distributions of the related cycle times generated by Witness Horizon during the simulation, where the parameters of the truncated Normal distribution are mean, standard deviation, minimum, and maximum values.

Due to the unavailability of specific data on the movement of empty containers, they are transported by terminal tractors to the dedicated storage area (see Fig. 2) but are not subsequently considered in the model for transport by truck or train. Therefore, we assume that they are shipped out of the system, effectively leaving the simulation once they reach the designated area and after spending a certain amount of time there.

Containers destined for rail transport are handled in the railyard with terminal tractors. These vehicles are like those already described used for handling from the berth to the storage areas, with different processing times depending on the distance between the storage area and the railyard, also reported in Table 4.

As already mentioned, all handling times of the terminal tractors are defined based on the terminal configuration shown in Fig. 5 and the type of containers. It is important to note that, in the case of refrigerated containers and those for dangerous goods, the handling times considered in the simulation model also include the necessary procedures required by regulations to avoid accidental risks and ensure the integrity of the goods. These procedures tend to reduce the transport time component of the total handling time. Once stored in their respective storage area, the model simulates the transport of containers to their destination.

For simulating train departure, we use the same procedure implemented in [17], where different policies and scenarios for train loading and departure are simulated and analyzed. In particular, the policy of allowing a maximum delay of 30 min in the departure time of trains is used in this study to allow an increase in the load level of trains if this is below a minimum threshold. In addition, a Uniform distribution of train departures over six days of the week, from Monday to Saturday, is taken into account, assigning an

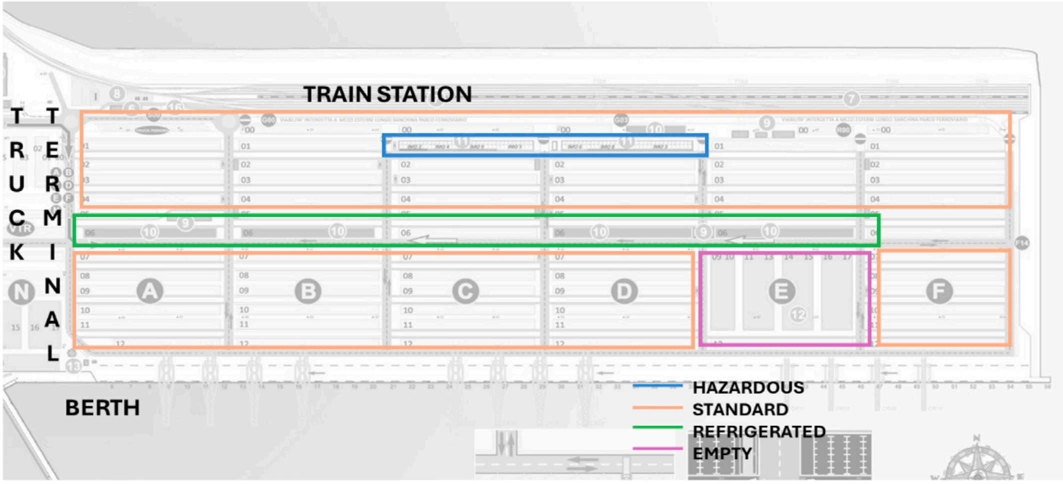

Fig. 5. Layout of PSA Genoa Pra terminal.
Source: Derived from [49].

equal number of trains departing each day, i.e. 10, and divided according to the distribution of destinations proposed in Table 2. Note that this freight rail service has some similarities with the methodology described in [45]. In the model, four RMGs moving containers from the rail yard to the trains are simulated. Their cycle time is represented by an Erlang distribution with an average value of 5 min and parameter k = 3. They unload the containers in priority order based on their delivery times, emptying one tier at a time. The RMGs are involved in loading the trains and check the destination of the container, verifying that the destination attribute of the container matches the destination of the train. In addition, the RMGs check that the loading percentage of the train does not exceed its capacity. Finally, for each of the four tracks, a buffer element and an assembly machine are used in the model to simulate each train. In this way, the buffer element allows counting the containers that are loaded into the corresponding train and calculates the load percentages, while the assembly machine allows the creation of the train element once the departure time is achieved. Each train is successively assigned to the destination intermodal terminal.

For the transport of containers leaving the terminal by truck, we consider the information reported in [50] that fixes a maximum limit of 2400 trucks per day that can be handled by the terminal, half of which are assumed for the import flow. This distribution, as done for terminal tractors, ensures that handling times remain within a realistic operational range while preventing extreme values that would be unrealistic in a terminal setting. Unlike container handling times, which depend on the container type, the truck cycle times are assumed to be independent of the specific container being transported, as the main influencing factor is the standardized terminal operations. Considering the location of the intermodal terminals serving the reference port for road transport listed in Table 2, the transport time for individual containers is assumed to be distributed according to a truncated normal distribution with parameters TNormal (30,5,20,60).

After the completion of maneuvering within the terminal, the truck places the container in the storage zone associated with the destination intermodal terminal, and the cycle starts again. The truck counter variable keeps track of the number of trucks processed daily, ensuring that the maximum capacity of the terminal is not exceeded.

To accurately represent the operational dynamics of the port of Genoa, the simulation model incorporates three types of shifts, defined in accordance with the Genoa Pra PSA guidelines [51]. These shifts reflect the schedules and constraints of the key activities simulated in our model, ensuring alignment with real practices, as follows:

- Quayside Shift: container handling follows the quayside operating schedule, active 363 days a year, 24 h a day, with activities suspended only on 25th of December and 1st of May.
- Train Shift: trains can depart from 06:00 on Monday until 06:00 on Sunday, while train loading operations are active every day from 06:00 to 22:00, except for 25th of December and 1st of May.
- Truck Shift: operating Monday to Friday from 06:00 to 22:00, on Saturdays from 06:00 to 14:00, while on Sundays, 25th of December and 1st of May it is closed.

5. Simulation experiments and results

5.1. Experimental setting

The simulation study is carried out on a system equipped with an 11th Gen Intel(R) Core(TM) i7-1165G7 processor operating at 2.80 GHz (2.80 GHz), a 64-bit operating system, and 16.0 GB of installed RAM (15.8 GB usable). As recommended when performing any discrete-event simulation study, see e.g. [52,53], several independent simulations are conducted to ensure the validity of the

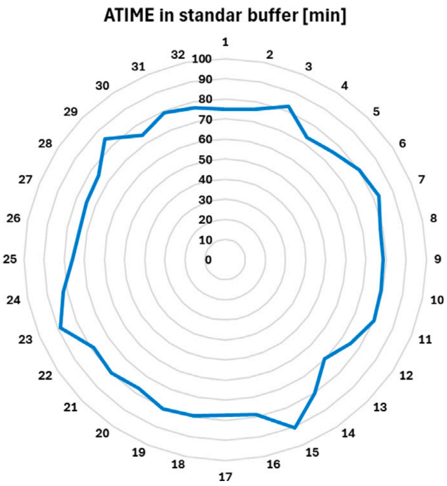

Fig. 6. Variance chart of Scenario 4 simulation.

steady-state conditions and to take into account the potential variability of the sampled measures for each scenario reported in Table 3.

The performance indices on which we focus our attention are the dwell time of containers waiting in the reference storage area, the maximum and average number of containers in it, and the utilization rate of the terminal tractors. These measures correspond, respectively, to the following predefined function in Witness Horizon:

- ATIME: average time spent by containers in storage areas (reefer, hazardous, standard), providing information on bottlenecks and flow efficiency.
- BMAX: maximum peak capacity used in storage areas, useful for assessing infrastructure and storage constraints.
- APARTS: average value of the number of containers waiting in a storage area. Compared to a simple arithmetic average, APARTS provides a more accurate view of load distribution over time, which is particularly useful for systems with dynamic flow variations.
- PUTIL:percentage of utilization of the terminal tractors for operations between berth to storage area and storage area to railyard.

For each scenario, 33 independent tests are performed. This number satisfies the $t_{n-1}-$Student confidence interval of the mean values of the above indices of interest, with a 95% degree of confidence in all considered scenarios. More precisely, for selecting the number of runs to execute for each scenario we assume the integer value rounded up given by the formula $n = \left(\frac{t_{1-\alpha/2,n-1}\cdot S}{E}\right)^2$, where E is half the desired confidence interval width. To give an idea, let us consider the validation of the developed simulation model conducted using Scenario 4, identified as the most balanced configuration among the six scenarios. To assess the performance of the model, the average dwell time of the containers in the standard storage area is analyzed. Using the $t_{32}-$ Student confidence interval with a 95% confidence level, we obtain a mean value equal to 78.67 min with a standard deviation of 4.23 min and derive from the t-Student table distribution the critical value $t_{32;0.05} = 1.694$. Therefore, the resulting confidence interval for this index is $78.67 \pm 1.694 * (4.23/\sqrt{33}) = 78.67 \pm 1,25$. Further, fixing $2 * E = 2.5$ min we have $n = (1.694 \cdot 4.23/1.25)^2 = 32{,}86$. The variance chart of Scenario 4 simulation test is reported in Fig. 6.

The simulation period spans a total of 15 months, including an initial warm-up phase of 3 months. Witness Horizon Experimenter module plays a crucial role in the process of automating the execution of different independent executions of the simulation model, enabling a predefined setup of parameters, such as number of runs, seed skip interval, warm-up duration, and total simulation time, as shown in Fig. 7. In particular, in the Configure section of Experimenter tool, data on simulation timing and seed change for independent simulations are fixed. In the section on entering scenarios, the relevant parameters in our study are selected and the characterizing values and types of indices to be classified as outcomes are entered.

5.2. Scenario analysis

The trend analysis in the six simulated scenarios relating to the container type (see Table 3) makes it possible to identify how changes in container composition affect the operational performance of the terminal, both in terms of storage area occupancy and equipment utilization. It should be noted that all scenarios are carried out with the parameters relating to the percentage of transport modes, size and status of containers shown in Table 1 remaining fixed. For a more accurate evaluation, the comparison between alternative scenarios (Scenarios 2–6) is carried out separately from the analysis of Scenario 1, which represents the current

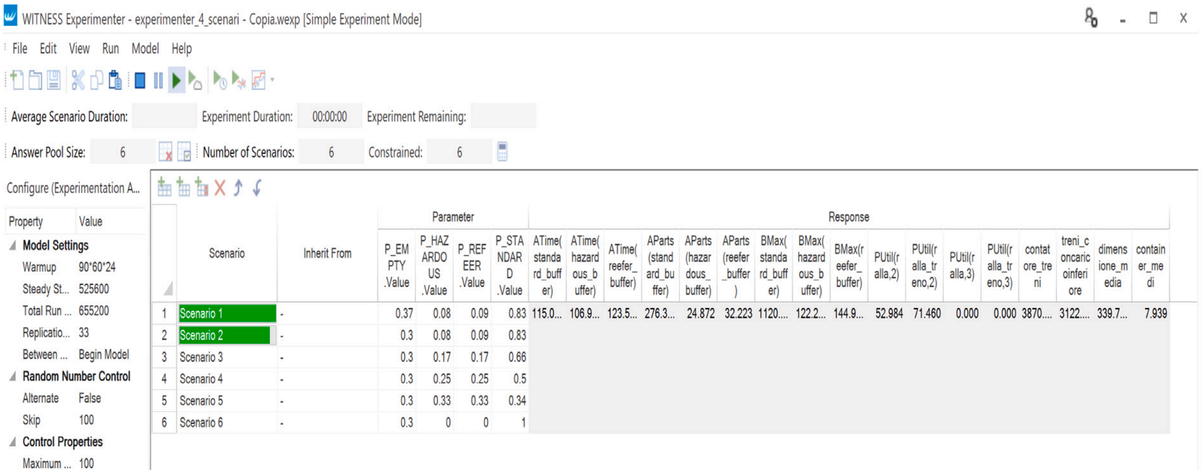

Fig. 7. Witness Horizon's Experimenter setting.

Table 5
Resulting values of Scenario 1.

ATIME storage area			APARTS storage area		
Standard	Hazardous	Reefer	Standard	Hazardous	Reefer
115.1	106.9	123.6	276	25	32
BMAX storage area			**PUTIL Terminal Tractors**		
Standard	Hazardous	Reefer	Berth-Yard	Yard-Railyard	
1121	122	145	53.0%	71.5%	

configuration of the terminal with the highest percentage of empty containers. The simulation values of the performance indices related to Scenario 1 are shown in Table 5.

Fig. 8 shows the ATIME trend, visibly revealing that Scenario 2, characterized by a predominance of standard containers (83% of non-empty containers), has the highest average dwell time among the alternative scenarios. This time is also higher than that of the terminal's reference configuration, which has a percentage of standard containers (83.3%) very similar to that of scenario 2 but also a 7% reduction in the total flow of containers circulating in the terminal compared to the other scenarios. Fig. 8 also shows that as the percentage of standard containers decreases in favor of reefer containers and those for dangerous goods, the average dwell times in the respective storage areas decrease progressively, until the types of container in Scenario 5 are equally distributed. In contrast, the ATIME value of Scenario 6, where it is at its lowest, shows that the handling operations are entirely focused on standard containers.

The APARTS and BMAX indicators are shown in Fig. 9. Readers can see that, although the two graphs represent different storage indicators, their trends are similar. Scenarios with higher percentages of reefer and hazardous containers have a higher average number of containers waiting, indicating that the handling of these categories, which have longer service times, necessarily involves a greater number of containers waiting in the storage area. However, based on the observed value of the BMAX indicator, there is no congestion in the storage area in any case. As observed for the ATIME indicator, in scenario 6 (100% standard) we have a lower value than in scenario 2 (83% standard), indicating that the presence of only standard containers facilitates handling and reduces the average time spent in the storage area.

Fig. 10 shows the analysis of terminal tractor occupancy time; it illustrates a significant influence of container type distribution on terminal tractor occupancy in the first leg. In particular, the utilization for movements from the quay to storage areas rises from 50.2% in Scenario 6 to 66.8% in Scenario 5, due to the strong impact of containers that subsequently leave the terminal by truck from the yard. It should be noted that utilization for movements from storage areas to the railway yard follows the opposite trend, showing only a slight downward trend as the percentage of refeer and hazardous containers increases, from 76.6% (100% standard containers) to 74.7% (34% standard containers). These results indicate that the presence of a higher percentage of reefer and hazardous containers in a terminal tends to lead to more intensive use of terminal tractors for internal handling, while terminal tractors used in the railway yard maintain a reasonably stable level of use, with no significant variations depending on the composition of the containers. This is also due to the fact that reefer and hazardous containers are on average allocated to areas closer to the railway yard and therefore require on average less transport time (see Fig. 5).

For a better comprehension of the behavior of the performance indicators under analysis, next, the best and worst cases among the presented alternative scenarios are compared with Scenario 1 to highlight any improvements or critical issues compared with

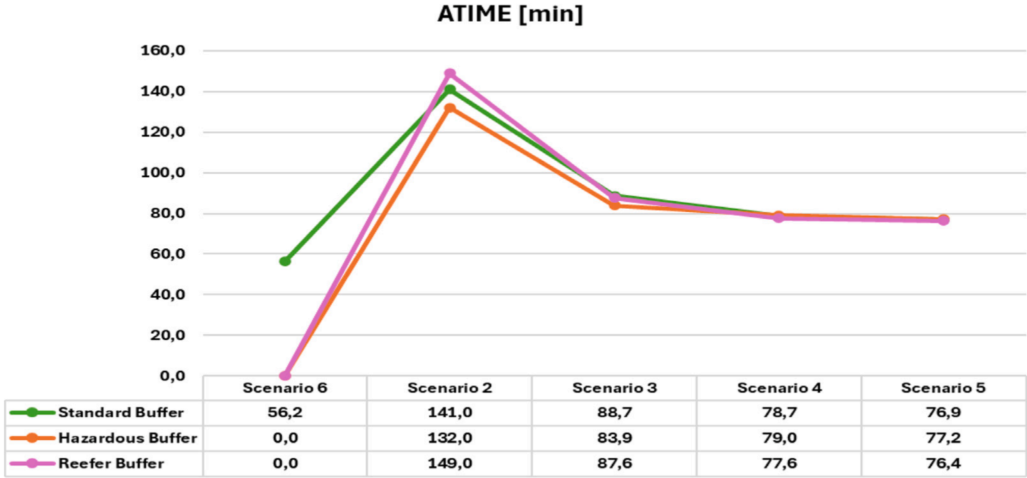

Fig. 8. Simulation results across scenario 2 to 6 of ATIME.

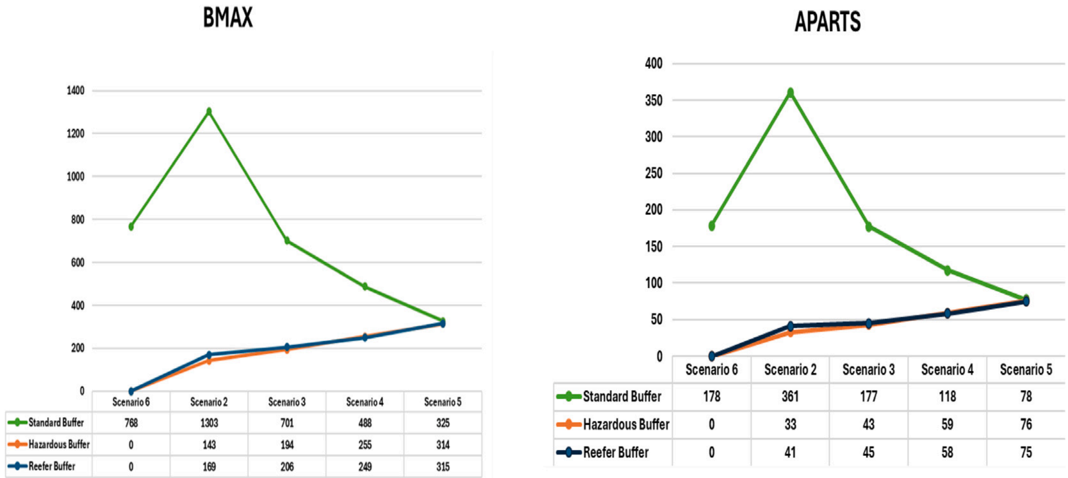

Fig. 9. Simulation results across scenario 2 to 6 of BMAX and APARTS.

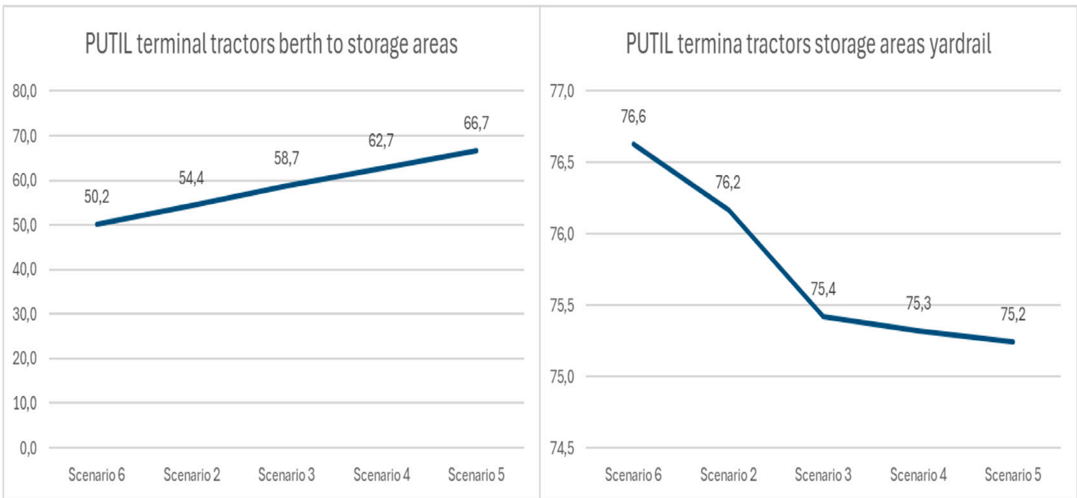

Fig. 10. Simulation results of scenarios 2 to 6 of average occupancy time of the terminal tractor from berth to yard and from yard to train.

Table 6
Comparison of the average values between the actual scenario and the best/worst ones.

	ATIME	APART	BMAX	PUTIL-yard	PUTIL-rail
Scenario 1	115.2	333	1121	53%	71,5%
Best scenario	6: 56.2	5: 178	5: 325	6: 50,2,9%	5: 75,2%
Worst scenario	2: 140,671	2: 435	2: 1303	5: 75,2,2%	6: 76,6%

the current situation. These values are synthesized in Table 6, where the average values for standard, refrigerated and hazardous containers are reported.

After analyzing the scenarios described above relating to different compositions of container types arriving by ship at the terminal, we decided to check whether the size of the containers also affects the indicators examined above. To this end, we considered different percentages of 20-foot containers out of the total, varying them from 10, 30, 50, 70 and 90% with reference to Scenario 1, i.e. the current one. However, we found that none of the indicators analyzed changed when these percentages varied.

5.3. Terminal management implications

The comparison between the current scenario, illustrated in Table 5, and the alternative ones examined shows how the composition of the container flow impacts the values of the indicators of interest in this study. In particular, in Scenario 2, characterized by a predominance of standard containers, all indicators relating to the storage area, i.e. dwell time, average number and maximum number of containers waiting, are higher than those in the other scenarios, including the one relating to the current configuration (Scenario 1). This result seems to indicate that the composition of around 80%–85% standard containers out of the total number of non-empty containers is the most unfavorable ratio considering the current allocation of resources and storage areas at the terminal. It should be noted that reducing empty containers in favor of standard containers, without adequate diversification, can lead to a slowdown in operations (transition from Scenario 1 to Scenario 2). Furthermore, Scenario 5, in which the proportion of reefer and hazardous containers is higher, significantly reduces the APARTS and BMAX indicators, highlighting that a more balanced management of container categories allows for smoother handling and better use of space in storage areas. Although standard containers are the easiest type to manage, this result seems to contradict what has just been presented for Scenario 2. However, from a resource management perspective, this result is not surprising, as all resources dedicated to container handling, whose number has already been set by management, are therefore allocated to standard containers. This trend could suggest that a single-type configuration, although unrealistic, could simplify the flow of operations and reduce the time containers spend in storage areas. However, concerning Scenario 6, in which all containers are standard, it should be noted that it represents the best configuration for the average time containers remain in storage areas. This result, which may seem to contradict what has just been highlighted, nevertheless confirms the critical threshold of 80%–85% standard containers out of the total, suggesting to management that a configuration with a single type of container, although unrealistic, could simplify container handling operations while reducing dwell time. In this case, in fact, all equipment would be dedicated to standard containers, making it possible to reorganize the storage space for containers, which currently occupies areas that are not contiguous. Further, it is important to note that the lower number of containers waiting in this scenario does not necessarily mean optimally managed handling, but rather a simpler operating model, due to the allocation of all resources to the handling of standard containers, which may not be applicable in a real-world context with heterogeneous flows.

Regarding the utilization rate of terminal tractors, a more diversified mix of container types requires greater use of handling equipment, with a significant percentage increase (from 50%to 66%) in the use of terminal tractors for transfers from the quay to the storage area. On the other hand, movements from the storage area to the railway yard follow a slightly downward trend, due to the greater proximity of the storage areas for reefer and hazardous containers to the railway yard. However, this result is consistent with the modal split of the terminal, with a clear predominance of road transport over rail transport.

Finally, the fact that the variation in the number of containers between 20 and 40 ft does not impact the indicators considered confirms that, with the same number of containers handled, this difference only affects the space occupied in the yard and not the waiting times or the utilization rate of the handling equipment.

6. Conclusions

This study analyses the impact of different compositions of import container types on the operational efficiency of a maritime terminal using a discrete event simulation model. The data used is derived from a terminal in the port network of Genoa, Italy, and integrated with a synthetic data generator, developed ad hoc for use in a simulation environment. While changes in the distribution of 20-foot and 40-foot containers results to be irrelevant, the findings reveal that the composition of container types affects the key performance indicators analyses, such as dwell time, average and maximum number of containers waiting in the storage areas, and terminal tractor workload. In particular, Scenario 2, which features a high predominance of standard containers, has the worst values of the indicators relating to storage areas. On the contrary, Scenario 5, characterized by a more uniform distribution of refrigerated and dangerous containers, shows significantly better values for these indicators. In the extreme but unrealistic case where only standard containers are present, the dwell time is the best overall. It should be noted that in this case, all handling equipment would be dedicated to standard containers, suggesting that terminal management should reorganize the storage space for standard containers, which currently occupy areas that are not contiguous. The composition of containers with approximately 80%–85% standard containers is the worst among the scenarios analyzed.

Regarding the terminal tractor occupancy rate, a more diversified composition of reefer and hazardous containers, increasing from 6% to 23%, results in an increase in their use for transfers from the quay to the storage area from 50% to 66%. This result, however, is consistent with the terminal modal split, which is heavily weighted toward road transport. Conversely, movements from the storage area to the rail yard follows a slightly decreasing trend. This is due to the greater proximity of the reefer and hazardous container storage areas to the rail yard.

A comparison with the current terminal configuration, represented by Scenario 1, indicates that, although the existing system maintains a balanced workload, there is room for improvement. Specifically, a final analysis of the observed indicator values shows that reducing the share of standard containers in favor of reefer and hazardous containers would allow for smoother handling within the terminal, ensuring reduced container waiting times and the use of terminal tractors, thus allowing for better utilization of the yard blocks allocated to the various container types.

The study therefore highlights the need for a strategic, data-driven approach to managing container flows in a terminal, ensuring that storage area allocation, transport vehicles, and operational workflows are aligned with the terminal's infrastructure capabilities. The insights from this study, which to the authors' knowledge is the first in the literature to conduct this type of sensitivity analysis, can therefore provide a valuable reference for port operators and logistics planners to improve productivity, reduce operating costs, and enhance service reliability in an increasingly competitive maritime logistics landscape. Indeed, the simulation results reported provide useful information to support operational decision makers regarding equipment and yard allocation.

From an academic perspective, future research could explore dynamic programming strategies and adaptive decision-making models that optimize container handling based on real-time demand fluctuations. Furthermore, the integration of machine learning techniques could further improve predictive capabilities, particularly with regard to more detailed information on import containers, enabling more efficient allocation of terminal resources.

Acknowledgments

This research work has been partially supported by the European Union—NextGenerationEU and by the Ministry of University and Research (MUR), National Recovery and Resilience Plan (NRRP), Mission 4, Component 2, Investment 1.5, project "RAISE—Robotics and AI for Socio-economic Empowerment" (ECS00000035).

On 12 September 2025, our dear friend and colleague Prof. Agostino Bruzzone, co-author of this article, passed away prematurely. We fondly remember his generous and assiduous work.

Data availability

Data will be made available on request.

References

[1] H.E. Haralambides, Gigantism in container shipping, ports and global logistics: a time-lapse into the future, Marit. Econ. Logist. 21 (1) (2019) 1–60.
[2] Y. Wu, R. Zhang, Evaluation model for a port hinterland intermodal freight network considering environmental impacts and capacity constraints, Transp. Res. Rec. 2677 (2) (2023) 462–478.
[3] K. Sanguri, S. Shankar, S. Punia, S. Patra, Hierarchical container throughput forecasting: The value of coherent forecasts in the management of ports operations, Comput. Ind. Eng. 173 (4) (2022) 108651.
[4] W. Liu, X. Zhu, L. Wang, S. Li, Flexible yard crane scheduling for mixed railway and road container operations in sea-rail intermodal ports with the sharing storage yard, Transp. Res. E 190 (2024) 103714.
[5] L. Zhen, W. Wang, S. Lin, L. Yang, S. Jiang, Joint berth and flexible storage space allocation in container tower ports, Transp. Res. E 194 (2025) 103942.
[6] Y. Wang, J. He, H. Yu, Y. Guo, Optimization of yard remarshalling operations in automated container terminals, Adv. Eng. Inform. 61 (2024) 102552.
[7] H. Bouzekri, N. Bara, G. Alpan, V. Giard, An integrated decision support system for planning production, storage and bulk port operations in a fertilizer supply chain, Int. J. Prod. Econ. 252 (2022) 108561.
[8] D. Pamucar, Ö.F. Görçün, Evaluation of the European container ports using a new hybrid fuzzy LBWA-CoCoSo'B techniques, Expert Syst. Appl. 203 (2022) 117463.
[9] N. Adler, G. Hirte, S. Kumar, H.M. Niemeier, The impact of governance on the technical efficiency of container ports, Transp. Res. A 199 (C) (2025) 104578.
[10] Q. Meng, J. Weng, L. Suyi, Impact analysis of mega vessels on container terminal operations, Transp. Res. Procedia 25 (2017) 187–204.
[11] E. Musso, A. Sciomachen, Impact of megaships on the performance of port container terminals, Marit. Econ. Logist. 22 (2020) 432–445.
[12] Y. Triska, E. Morosini Frazzon, V. Macowski Durski Silva, Proposition of a simulation-based method for port capacity assessment and expansion planning, Simul. Model. Pr. Theory 103 (2020) 102098.
[13] S.-H. Hur, C. Lee, H.-S. Roh, S. Park, Y. Choi, Design and simulation of a new intermodal automated container transport system (ACTS) considering different operation scenarios of container terminals, J. Mar. Sci. Eng. 8 (4) (2020) 233.
[14] M. Stojaković, E. Twrdy, A simulation approach to the definition of the subsystems parameters in small container terminals, J. Mar. Sci. Eng. 9 (9) (2021) 1023.
[15] L. Dumetz, J.-F. Audy, M. Rönnqvist, R. Azouzi, Simulation-based evaluation of road transportation logistics in a dry port with topographic challenges, J. Shipp. Trade 9 (1) (2024) 24.
[16] L. Zhang, Research on simulation modeling of container terminal logistics system based on WITNESS, in: 2022 International Conference on Industrial IoT, Big Data and Supply Chain, IIoTBDSC, IEEE, 2022, pp. 173–178.
[17] A. Giulianetti, M. Gotelli, A. Sciomachen, Comparative analysis of train departure strategies in a container shipment, Logistics 8 (3) (2024) 92.

[18] N.M. Abourraja, N. Rouky, M. Kornevs, S. Meijer, N. Kringos, A simulation-based decision support framework devoted to Ro–Ro terminals: Design, implementation and evaluation, Comput. Ind. Eng. 180 (2023) 109248.
[19] R. Iannone, S. Miranda, L. Prisco, S. Riemma, D. Sarno, Proposal for a flexible discrete event simulation model for assessing the daily operation decisions in a Ro–Ro terminal, Simul. Model. Pr. Theory 61 (3) (2016) 28–46.
[20] M.N. Abourraja, N. Kringos, S. Meijer, Exploiting simulation model potential in investigating handling capacity of Ro–Ro terminals: The case study of Norvik seaport, Simul. Model. Pr. Theory 117 (2022) 102513.
[21] E.D. Özkan, S. Nas, N. Güler, Capacity analysis of Ro–Ro terminals by using simulation modeling method, Asian J. Shipp. Logist. 32 (3) (2016) 139–147.
[22] S. Maldonado, R.G. González-Ramírez, F. Quijada, A. Ramírez-Nafarrate, Analytics meets port logistics: A decision support system for container stacking operations, Decis. Support Syst. 151 (2019) 84–93.
[23] S.W. Cho, H.J. Park, A. Kim, J.H. Park, GMM-based online optimization for container stacking in port container terminals, Comput. Ind. Eng. 173 (2022) 108671.
[24] N.R. Dayama, A. Ernst, M. Krishnamoorthy, V. Narayanan, N. Rangaraj, New models and algorithms for the container stack rearrangement problem by yard cranes in maritime ports, EURO J. Transp. Logist. 6 (4) (2017) 307–348.
[25] A. Bruzzone, M. Massei, K. Sinelshnkov, Enabling strategic decisions for the industry of tomorrow, Procedia Manuf. 42 (2020) 548–553.
[26] C. Zhou, N. Ma, X. Cao, L.H. Lee, E.P. Chew, Classification and literature review on the integration of simulation and optimization in maritime logistics studies, IISE Trans. 53 (10) (2021) 1157–1176.
[27] L. Kong, M. Ji, Mathematical modeling and optimizing of yard layout in automated container terminals, Expert Syst. Appl. 258 (2024) 125117.
[28] J. Jin, T. Cui, R. Bai, R. Qu, Container port truck dispatching optimization using Real2Sim based deep reinforcement learning, European J. Oper. Res. 315 (1) (2024) 161–175.
[29] J. Zhu, W. Zhang, L. Yu, X. Guo, A novel multi-attention reinforcement learning for the scheduling of unmanned shipment vessels (USV) in automated container terminals, Omega 129 (2024) 103152.
[30] M.R.F. da Silva, I.R.S. Agostino, E. Morosini Frazzon, Integration of machine learning and simulation for dynamic rescheduling in truck appointment systems, Simul. Model. Pr. Theory 125 (2023) 102747.
[31] S. El Mekkaoui, L. Benabbou, A. Berrado, Machine learning models for efficient port terminal operations: Case of vessels' arrival times prediction, IFAC-PapersOnLine 55 (10) (2022) 3172–3177.
[32] C. Maervoet, T. Vanelslander, M. Vervoort, Data analysis for more accurate cargo ship ETA's: a model for ETA deviation prediction, WMU J. Marit. Aff. 23 (3) (2024) 293–327.
[33] Y. Wu, L. Wu, X. Yang, S. Chen, H. Xie, Adaptive allocation method of terminal container parameters based on evolutionary game, in: International Conference on Neural Computing for Advanced Applications, Springer, 2024, pp. 17–27.
[34] Y. Tang, Z. Ye, Y. Chen, J. Lu, S. Huang, J. Zhang, Regulating the imbalance for the container relocation problem: A deep reinforcement learning approach, Comput. Ind. Eng. 191 (2024) 110111.
[35] T.N. Mathias, H. Inutsuka, T. Shinoda, Y. Sugimura, Operational performance evaluation of a container terminal using data mining and simulation, Asian Transp. Stud. 10 (2024) 100127.
[36] R. Raeesi, N. Sahebjamnia, S.A. Mansouri, The synergistic effect of operational research and big data analytics in greening container terminal operations: A review and future directions, European J. Oper. Res. 310 (3) (2023) 943–973.
[37] A. Bruzzone, A. Sciomachen, M. Gotelli, A. Giovannetti, A. Giulianetti, F. Shamlu, Scenario simulation to investigate new solutions for port terminals and plants based on intelligent data fusion and supply chain modelling, in: Proceedings of the International Conference on Harbor, Maritime and Multimodal Logistic Modelling and Simulation, Tenerife, Spain, 2024, pp. 18–20.
[38] M. Kastner, O. Grasse, Synthetically generating traffic scenarios for simulation-based container terminal planning, 2024.
[39] M. Kastner, O. Grasse, C. Jahn, Container flow generation for maritime container terminals, in: International Conference on Dynamics in Logistics, Springer, 2022, pp. 133–143.
[40] ConFlowGen, ConFlowGen: Container flow generation tool, 2024, https://conflowgen.readthedocs.io/en/latest/. (Accessed 20 December 2024).
[41] D. Majnarić, S. Baressi Šegota, N. Anđelić, J. Andrić, Improvement of machine learning-based modelling of container ship's main particulars with synthetic data, J. Mar. Sci. Eng. 12 (2) (2024).
[42] A. Waller, Witness simulation software, in: Proceedings of the Winter Simulation Conference, 2012, pp. 1–12.
[43] Lanner Group Ltd., Lanner witness simulation software, 2025, https://www.lanner.com/en-us/technology/witness-simulation-software.html.(Accessed 15 January 2025).
[44] A. Cartenì, S. De Luca, Tactical and strategic planning for a container terminal: Modelling issues within a discrete event simulation approach, Simul. Model. Pr. Theory 21 (1) (2012) 123–145.
[45] A. García, I. García, A simulation-based flexible platform for the design and evaluation of rail service infrastructures, Simul. Model. Pr. Theory 27 (2012) 31–46.
[46] A. Bruzzone, A. Sciomachen, Simulating operating performance of alternative configurations of LNG bunkering stations, Sustainability 15 (13) (2023) 9940.
[47] T. Nong, Research on the application of witness in logistics management of container terminals, in: Proceedings of the 2023 International Conference on AI and Metaverse in Supply Chain Management, 2023, pp. 1–5.
[48] Ports of Genoa, Report traffici Q4 2023, 2024, https://www.portsofgenoa.com/it/chi-siamo/porto-numeri.html. (Accessed 15 October 2024).
[49] PSA Genova Pra, PSA genova pra official website, 2024, https://www.psagp.it. (Accessed 15 October 2024).
[50] PSA Genova Pra, PSA genova pra online portal, 2024, https://online.psagp.it/it. (Accessed 25 October 2024).
[51] Global PSA, Sustainability report 2023, 2024, https://www.globalpsa.com/sustainability-report. (Accessed 20 October 2024).
[52] J. Banks, J. Carson, B. Nelson, Discrete-Event System Simulation, Pearson Educational Limited, 2013.
[53] A.M. Law, Simulation Modelling and Analysis, fifth ed., McGraw Hill, New York, NY, USA, 2015.